Prediction Model of Flood Risk Management: Fuzzy Logic Approach

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Application of Fuzzy Logic Approach in Generation of Automatic Flood Warnings by SMS

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Abstract: This paper presents the practicability of using fuzzy logic approach for developing a prediction model of flood risk identification in order to provide early warning to peoples about the possibility of flooding. Although there are different type of methods to predict weather, but it is not easy to determine whether flooding will occur or not. Hence, early action should be established to obtain any information in order to reduce the risk of property damage and loss of life. Therefore, the main purpose of the study was to investigate the relationship between water level and climate condition, as well as to evaluate the viability of using fuzzy logic expert system in predicting the flood risk level. Experimental values were taken in the laboratory for flood detection system. A fuzzy logic expert system model based on Mamdani approach was subsequently developed to predict the flood risk level in terms of control action. The study revealed that the developed fuzzy system was able to predict the flood risk level in terms of control action within high accuracy. Verification of the system was carried out through theoretical, simulation and experimental data.

Keywords: Flood risk, Risk of property, Fuzzy logic, Water level, Climate.

Introduction

Floods are considered as one of the most damaging and dangerous natural hazards when it is over the minimum level and hence cause many disasters. To overcome this issue, the flood detected system is developed in order to resolve the existing problems that occur from floods (1-5). However, flood detection system is undoubtedly a challenging arena of hydrology; in particular, the rainfall-water level rise relationship has been recognized to be nonlinear. Flood detection system is the method used to detect the rising water level in the resident area. When the water rises, circuit sends signal to the system and the system then informs the rising of water level to the users using short messaging service (SMS). Thus, researchers are working toward producing more information from natural resources such as wind characteristics, climate condition, etc. that can be reasonable and workable affecting the environment and ecological system significantly [6-9]. In addition, the signal system can be employed to prevent short circuits which may cause fire or electric shock to the residents who are concerned saving their property and important documents from damage due to flooding. The main purpose of the flood detection system is to avert or minimize loss of life. Hence, this vision is expanded and defined the purpose of the flood risk level or detection system as a means of establishing public safety, to reduce damage to property and to relieve public anxiety. Therefore, to find out effective information, a prototype of flood detection system has been developed in the Laboratory of Faculty of Engineering, University Selangor. Several experiments have been carried out providing water to show the water rises till the level that contributes a signal to the circuits. Various techniques have been proposed in the literature [10-15] to forecast the flood level. At present artificial intelligence system such as machine learning, neural network, genetic algorithms, etc., have largely been used in different areas [16-24]. However, all the parameters depend on many data. On the other hand, fuzzy logic expert system (FLES) might play an important role since it uses expert knowledge on controlling the particular system, it is flexible and it correctly estimates the unknown values of the modeled data, often improve performance and it has high level expression capability [25-26]. The choice of fuzzy set theory as the main analytical tooling is due to the good applicability of this approach to uncertain weather conditions. Generally, fuzzy sets use the linguistic expressions instead of numerical values as compared to classical data sets. It is reported that the flood detection could be measured by performing experiment which could be expensive. Because of this reason, to accurately predict the flood risk level in terms of control action, a fuzzy logic expert system model based on Mamdani approach has been developed in a given operation system and weather conditions.

For implementation of fuzzy theory into the system, the fuzzy toolbox from MATLAB has been used. Four fundamental units such as fuzzification unit, the knowledge base (rule base), the inference engine and defuzzification unit are necessary for the successful application of fuzzy modeling approach. This work presents the construction of fuzzy knowledge-based model using *if-then* rules for the prediction of flood detection system based on Mamdani approach.

Materials and Methods

Figure 1 illustrates the basic components of flood detection system. The system is comprised of distribution fuse box, GSM modem, transmitter box, electronics box, and receiver box. Transmitter and receiver boxes are used for the first stage system; while the electronics box is used for the second and third stages system. Aquarium is used to indicate rising water levels. Mini float switch is used as a sensor for the first stage; while the copper plate is used as a sensor for the second and third stages. Furthermore, flood detection system is designed into two stages known as first and second stage. The first stage is designed to give early warning that the flood is ensuing. In this stage, software and hardware have been designed and developed. Software design is divided into three sections, namely the sending, receiving and sending a short message to the persistent phone number using GSM modem. On the other hand, hardware is developed with transmit and receive circuits. The second and third stages are designed to cut off power supply into the miniature circuit breaker (MCB). Electronic circuits are used to cut off the electricity supply in case of emergency. The schematic design is converted into the PCB layout before being printed and transferred to the PCB board. The main components in this circuit are the PIC16F876A, RF Transmitter, buzzer and mini float level switch. The block diagrams of the transmitter and receiver layouts are shown in Fig. 2 and 3, respectively.

Fig. 1: Flood detection system

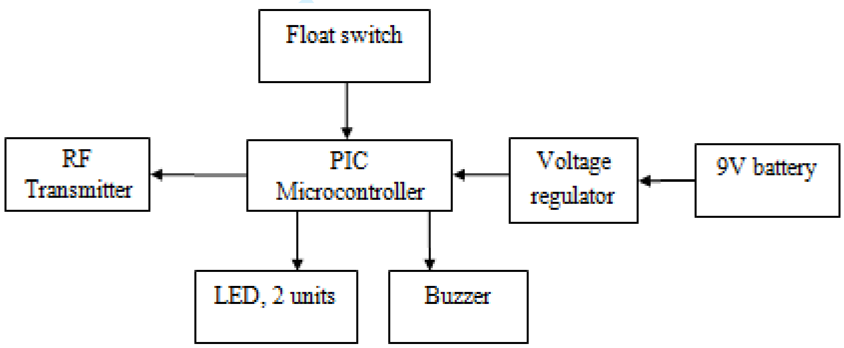

Fig. 2: Transmitter block diagram

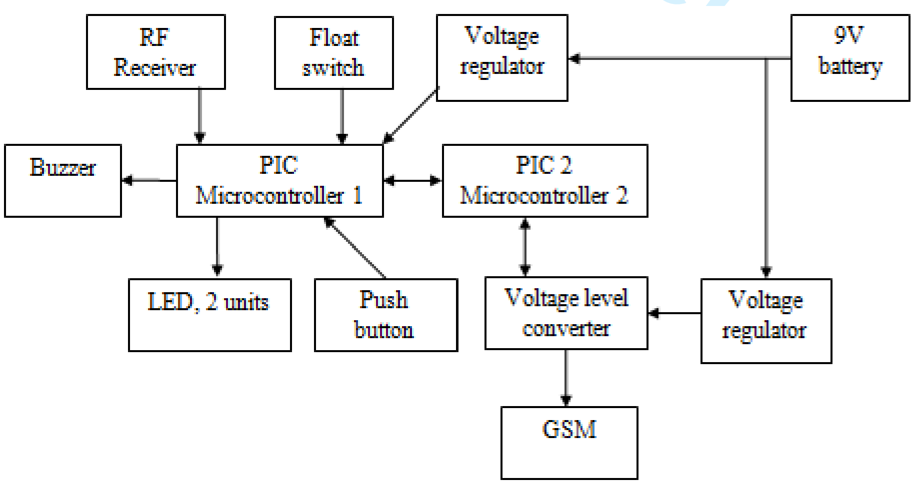

Fig. 3: Receiver block diagram

Fuzzy Logic Expert System

Fuzzy logic expert system (FLES) generally comprises four principal components [26-28]. They are: (1) Fuzzification- which takes the crisp numeric inputs and coverts them into the fuzzy form, (2) Rule base- which holds a set of *if-then* rules, (3) Inference-which creates the control actions, and (4) Defuzzification-which calculates the actual (crisp) output. In general, rule base is a set of logical statements for the linguistic variables used in FLES with the membership functions created from statistical data, expert's appraisals and so on.

For implementation of fuzzy values into the system, water level (WL) and climate condition (CL) are used as input parameters and control action (CA) is used as output as shown in Fig. 4. For fuzzification of these factors the linguistic variables very low (VL), low (L), low medium (LM), medium (M), high medium (HM), high (H) and very high (VH) are used for the inputs. While for control action (CA), the linguistic variables are S1 (started action for flood situation), S2 (started flood alarm system), S3 (send SMS to user stating that flood is detected), S4 (MCB supply disconnected), and S5 (MCB disconnected and emergency light switches on) are used for the output. In this study, a Mamdani max-min inference approach and the center of gravity defuzzification method have been used because these operators assure a linear interpolation of the output between the rules [25]. The Mamdani fuzzy inference system employs the individual rule based inference scheme, and derives the output subjected to a crisp input. Within the framework of the present investigation, triangular shaped membership functions are used for both input and output variables because of their high accuracy. Selection of the membership functions and their formations is based on the system knowledge, expert's appraisals, and experiment conditions. For the input and output parameters, a fuzzy associated memory is formed as regulation rules. Total of 25 rules have been formed. Parts of the developed rules are shown in Table 1.

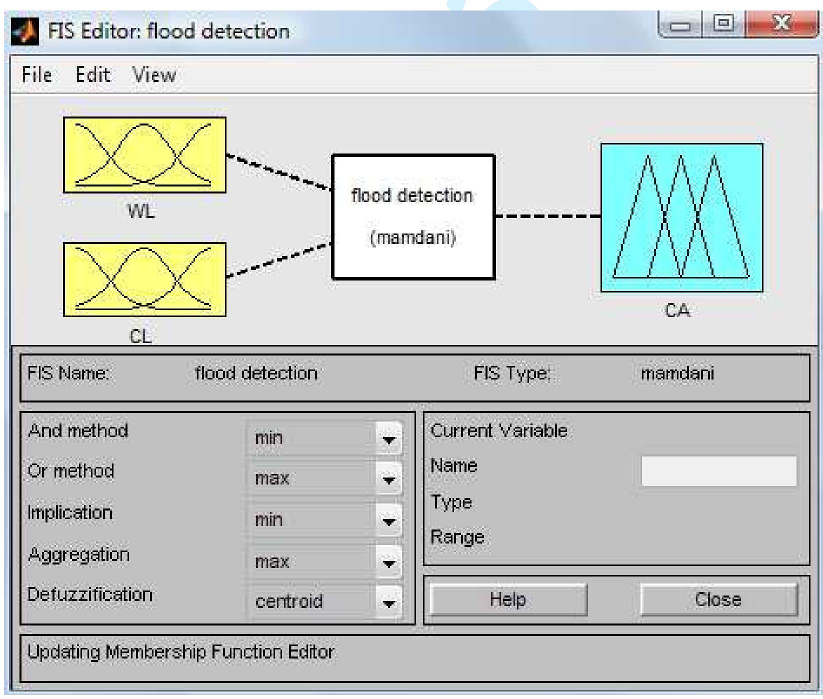

Fig. 4: The structure of the fuzzy inference system (FIS)

Table 1. Inference rules of controller parameters.

Rules	Input variables		Output variable
	WL	*CL*	*CA*
1	VL	VL	S1
-----	-----	-----	-----
5	VL	VH	S2
-----	-----	-----	-----
14	M	H	S3
-----	-----	-----	-----
20	H	VH	S4
-----	-----	-----	-----
25	VH	VH	S5

There is a degree of membership for each linguistic term that applies to that input variable. Fuzzifications of the used factors are made by aid follows functions.

$$WL(i_1) = \begin{cases} i_1; & 0 \le i_1 \le 1200 \\ 0; & otherwise \end{cases} \quad (1)$$

$$CL(i_2) = \begin{cases} i_2; & 0 \le i_2 \le 12 \\ 0; & otherwise \end{cases} \quad (2)$$

$$CA(o_1) = \begin{cases} o_1; & 0 \le o_1 \le 1 \\ 0; & otherwise \end{cases} \quad (3)$$

In Eqns. (1)-(3), i_1 is the first input variable (*WL*), i_2 is the second input variable (*CL*), and o_1 is the output variable (*CA*). Prototype triangular fuzzy sets for the fuzzy variables, namely, water level (*WL*), climate condition (*CL*) and control action (*CA*) are set up using MATLAB FUZZY Toolbox. The membership values obtained from the above formulae are shown in the Figs. 5-7. The degree of *WL* is measured in mm from 0 to 1200 mm, *CL* is measured in degree from 0 to 12 degree, and *CA* is measured in scale form from 0 to 1, respectively.

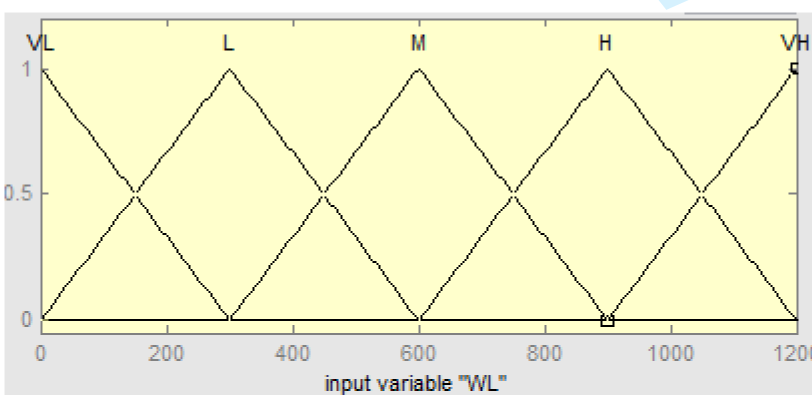

Fig. 5: Prototype membership functions of input variable WL

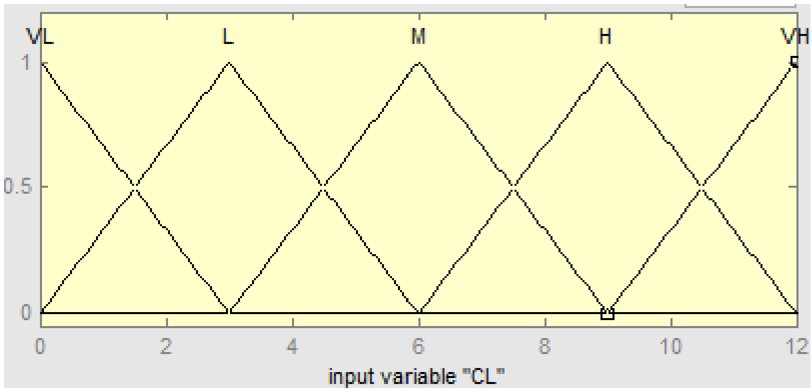

Fig. 6: Prototype membership functions of input variable CL

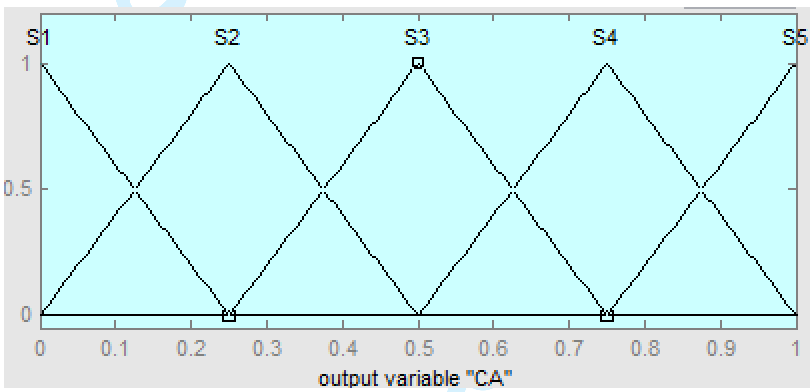

Fig. 7: Prototype membership functions of output variable CA

It is noted that the detection of the weather-related condition or environmental properties for flood detection system is a higher-order challenge. Consequently, this condition may affect on prediction tasks for flood detection system. However, several options of rules bases of different sizes are studied for the input variables under consideration. The formation of membership functions is considered from the statistical data, human expertness, and system knowledge. The coefficients of membership functions for the fuzzy inference (FIS) parameters are given in Table 2-4.

Table 2. Coefficients of membership functions for FIS parameter of WL

Linguistic variables	Type	Coefficients (mm)		
		c_1	c_2	c_3
VL	Z-shaped	0	300	-
L	Triangular	0	300	600
M	Triangular	300	600	900
H	Triangular	600	900	1200
VH	S-shaped	900	1200	-

Table 3. Coefficients of membership functions for FIS parameter of CL

Linguistic variables	Type	Coefficients (degree)		
		c_1	c_2	c_3
VL	Z-shaped	0	3	-
L	Triangular	0	3	6
M	Triangular	3	6	9
H	Triangular	6	9	12
VH	S-shaped	9	12	-

Table 4. Coefficients of membership functions for FIS parameter of CA

Linguistic variables	Type	Coefficients		
		c_1	c_2	c_3
S1	Z-shaped	0	0.25	-
S2	Triangular	0	0.25	0.5
S3	Triangular	0.25	0.5	0.75
S4	Triangular	0.5	0.75	1
S5	S-shaped	0.75	1	-

To illustrate the fuzzification process, linguistic expressions and membership function of water level (WL) obtained from the developed rules and with Table 2 is presented analytically as follows:

$$\mu_{VL}(WL) = \begin{Bmatrix} 1; & x \le 0 \\ \dfrac{300 - x}{300 - 0}; & 0 \le x \le 300 \\ 0; & x\rangle 300 \end{Bmatrix} \tag{4}$$

$$\mu_{L}(WL) = \begin{Bmatrix} \dfrac{x - 0}{300 - 0}; & 0 \le x \le 300 \\ \dfrac{600 - x}{600 - 300}; & 300 \le x \le 600 \\ 0; & x\rangle 600 \end{Bmatrix} \tag{5}$$

$$\mu_{M}(WL) = \begin{Bmatrix} \dfrac{x - 300}{600 - 300}; & 300 \le x \le 600 \\ \dfrac{900 - x}{900 - 600}; & 600 \le x \le 900 \\ 0; & x\rangle 900 \end{Bmatrix} \tag{6}$$

$$\mu_H(WL)=\begin{cases}\dfrac{x-900}{900-600}; & 600\le x\le 900\\ \dfrac{1200-x}{1200-900}; & 900\le x\le 1200\\ 0; & x\rangle 1200\end{cases} \tag{7}$$

$$\mu_{VH}(WL)=\begin{cases}0; & x\le 900\\ \dfrac{x-900}{1200-900}; & 900\le x\le 1200\\ 1; & x\rangle 1200\end{cases} \tag{8}$$

Similarly, the linguistic expressions and membership functions of other parameters could be calculated. In defuzzification stage, truth degrees (μ) of the rules are determined for the each rule by aid of the min and then by taking max between working rules.

To comprehend fuzzification, an example is considered. For crisp input WL = 400 mm and CL = 7 degree, the rules 8, 9, 13 and 14 are fired. The firing strength (truth values) α of the four rules are obtained as

$$\alpha_8=\min\{\mu_L(WL),\mu_M(CL)\}=\min(0.67,0.67)=0.67$$
$$\alpha_9=\min\{\mu_L(WL),\mu_H(CL)\}=\min(0.67,0.33)=0.33$$
$$\alpha_{13}=\min\{\mu_M(WL),\mu_M(CL)\}=\min(0.33,0.67)=0.33$$
$$\alpha_{14}=\min\{\mu_M(WL),\mu_H(CL)\}=\min(0.33,0.33)=0.33$$

Therefore, the membership functions for the conclusion reached by rule (8), (9), (13) and (14) are obtained as follows

$$\mu_8(CA)=\min\{0.67,\mu_{S2}(CA)\}$$
$$\mu_9(CA)=\min\{0.33,\mu_{S2}(CA)\}$$
$$\mu_{13}(CA)=\min\{0.33,\mu_{S3}(CA)\}$$
$$\mu_{14}(CA)=\min\{0.33,\mu_{S3}(CA)\}$$

Rajasekaran & Vijayalakshmi [28] has reported that in many conditions, for a system whose output is fuzzy, it can be simpler to receive a crisp decision if the output is represented as a single scalar quantity. This conversion of a fuzzy set to single crisp output in order to take action is called defuzzification. In this stage, the output membership values are multiplied by their corresponding singleton values and then are divided by the sum of membership values to compute CA^{crisp} as follows

$$CA^{crisp}=\frac{\sum_i b_i\mu_{(i)}}{\sum_i \mu_{(i)}} \tag{9}$$

where b_i is the position of the singleton in the i th universe, and $\mu_{(i)}$ is equal to the firing strength of truth values of rule i. Using Eq. (9) with Fig. 7, the crisp output of CA is obtained as 0.35 and hence, control action is taken accordingly.

Results and Discussion

The fuzzy control surface for the set associations described in the preceding tables is shown in Fig. 8, where the output variable “CA” is developed from the corresponding rules base against its two inputs of WL and CL. The surface plot depicts the impacts of the flood detection parameters. This is the mesh plot results from the interpolation of the rule base with twenty five rules. The plot is used to check the rules and the membership functions. If necessary, the rule base for the fuzzy sets is modified until the output curves are desired. Fig. 8 shows that the surface represents in a compact way all the information in the fuzzy logic system. Hence, it can be noted that this representation is limited in that if there are more than two inputs it becomes difficult to visualize the surface. Furthermore, this figure simply represents the range of possible defuzzified values for all possible inputs WL and CL. It also shows that as the water level (WL) and climate condition (CL) increase, there is concomitant increase in control action (CA) to be taken and vice versa as expected. It shows that control action reaches the peak when the water level and climate condition both reach their respective maximum level, although the effect is less prominent at the higher level of climate condition since water level is very high and flood has occurred. Consequently, control action reaches the dip when the water level and climate condition both reach their respective minimum level.

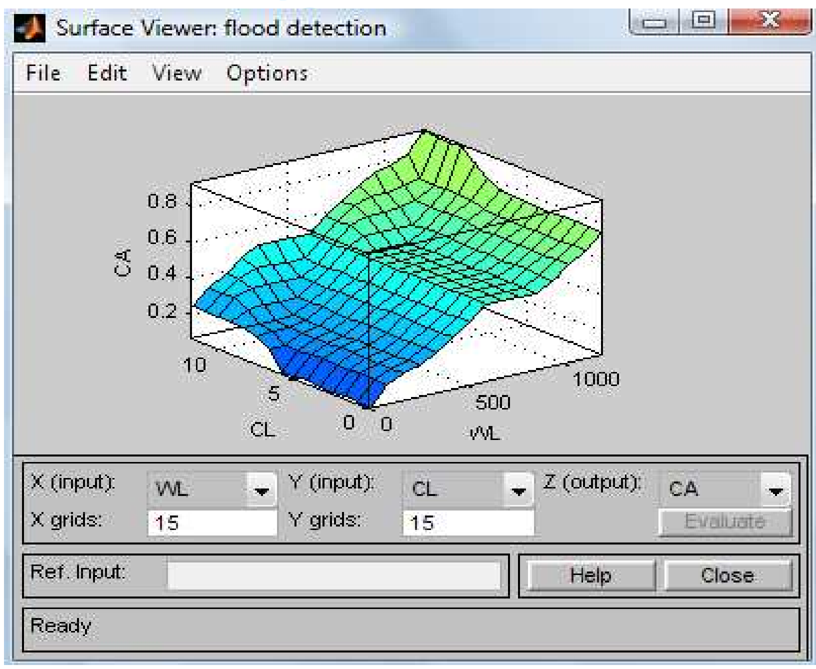

Fig. 8. Control surfaces of the fuzzy inferring system

The validation of the developed system in this study has been carried out by making comparison between theoretical, simulation and experimental data. In the first stage, the analysis is made in time taken for the transmission of short messaging system (SMS) to the users. Users receive a short message in three different conditions: the users receive a short message that the system has started by activating the system, the users receive a second short message that the flooding is detected when the flood occurs, and finally, the users receive a third short message that the flooding level is safety condition. For the convenient, the short message transmission time is calculated as follows:

The first short message is consisted of 19 characters where each character used 7-bit data to transmit as follows:

$$[(19 \times 7)/ 184] \times 235.5 \text{ ms} = 170.2255 \text{ ms}$$

Similarly for the second and third short messages are comprised with 18 and 22 characters for which transmission times are 161.2663 ms and 197.1033 ms, respectively.

Results of the theoretical calculations are displayed in graphical form as shown in Fig. 9. From the graph it can be stated that the arrival time depends on the quantity used for characters. Many characters could be used, hence, a lot of time needs to be taken into consideration. However, the MCB trips in the event short circuit. Meanwhile, RCCB also trips during the leakage current to earth. If this happens it may damage the electrical equipment at home. In order to overcome the damage of equipment, flood detection system could function as a current break into the MCB when flood occurs. For the second and third stages, the analysis has been made into two conditions: without water and with water. Each state is developed with three sections: theoretical, simulation and practical. The simulation result has been obtained using MULTISM software and the output voltage readings have been taken from the multi-meter. Resistance of multi-meter is set by the user. On the other hand, the practical results have been obtained based on the readings taken from a digital multi-meter and the resistance is set by the factory.

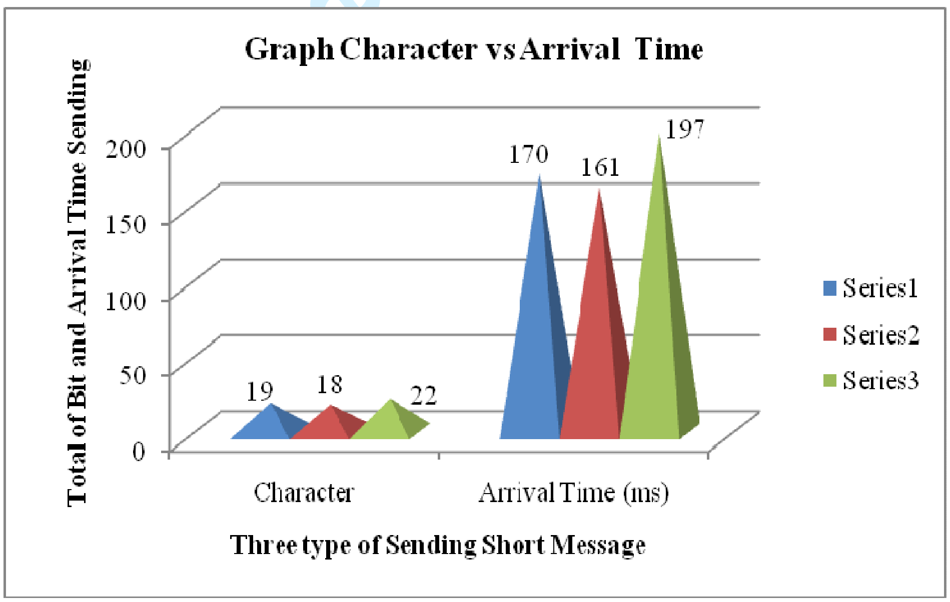

Fig. 9: Graph output of quantity character vs. arrival times

The overall results from the three analyses are presented in tabular form (Table 5) and in graphical form (Fig. 10). The data used in theoretical calculation has been taken from datasheet of CD4011 and BC457. Furthermore, CD4011 ICs have been used because the voltage on the network is 9V. However, it is noted that the simulation result is different between theoretical and practical result. This is because the specification of building materials in the MULTISM software which is not the same as that used in the theoretical and practical. The use of a multi-meter is also different between simulations and practical in term of resistance.

From the laboratory experiment, the transmission of short messaging system (SMS) to the users was observed using microcontroller attached on the system. The use of SMS, however, shows some delay at certain busy hour time, due to the unavailability and traffic busy of GSM network. However, from the results it can be concluded, that by using the minimum input voltage of the circuit, the incoming voltage can be disconnect at the MCB. Moreover, the output voltage readings taken from the multi-meter was found according to the desired level.

Table 5: Result of voltage output from three analyses

Pin	Without Water (V_{OUT})			With Water (V_{OUT})		
	Theoretical	Simulation	Practical	Theoretical	Simulation	Practical
1	0.82	0.75	0.73	0.82	0.75	0.75
3	8.1	14.98	8.08	8.1	14.996	8.47
4	7.29	7.01	7.78	-0.76	0	0
5	8.1	14.98	8.08	8.1	14.996	8.47
6	-0.76	0	0	7.29	7.01	8.55
8	7.29	7.01	7.67	-0.76	0	0
9	0	0	0	0.82	0.75	0.73
10	-0.76	0	0	7.29	7.01	8.55
4.7kΩ	6.59	6.26	6.76	-1.46	0	0
V_{CE}	0.6	0.0238	0.0967	8.3	6	8.62

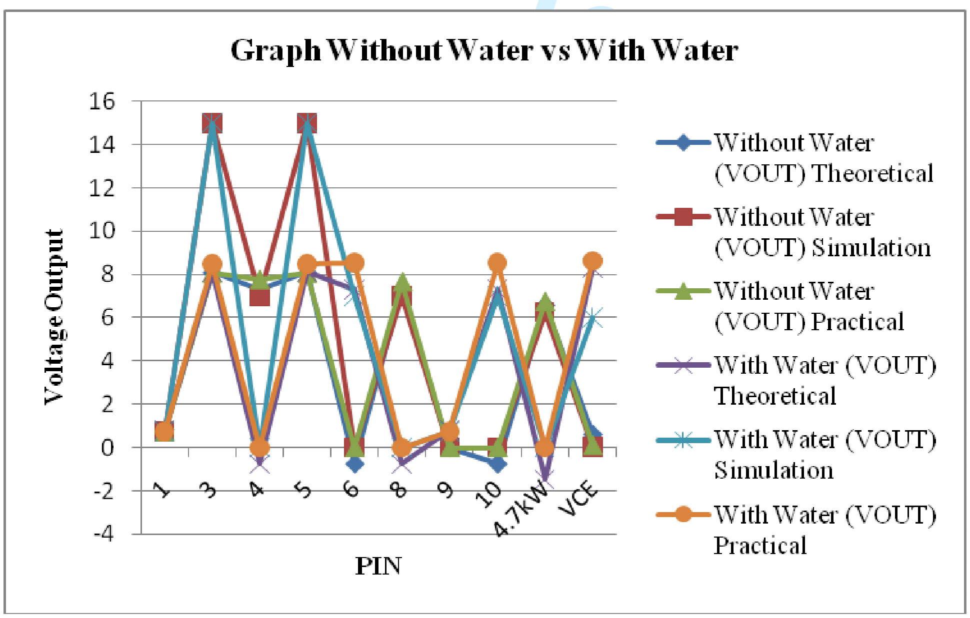

Fig. 10: Variation of voltage output with the variation of PIN positions

Conclusions

A prototype flood risk management system is developed to detect the rising water level in the resident area and hence provide early warning to peoples about the possibility of flooding using short messaging services. The results indicate that there is less variability of the measured and simulated data of the flood risk level detection system. More specifically, the conclusions of this study made based on the water level available are as follows:

(a) The developed prototype flood risk system indicates three short messaging services in three conditions.
(b) The developed system could detect the increase in water level due to and cut off sources of electricity in the house successfully.
(c) Flood risk level can be predicted from the model developed by Fuzzy expert system.

This work has demonstrated the viability of the developed FLES model to predict flood risk level within high accuracy without needing to undergoing laborious experimental work in a variety of environmental conditions with many uncertanties which can be noneconomical and time consuming.

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Future Research

The author is developing a more sophisticated flood risk management system which is adopting the same concept and using hybrid intelligent approach of Adaptive Neuro-Fuzzy Inference System (ANFIS). The prototype system will be used for the river side residents who are always in danger. The statistical analysis will be conducted in order justify the environment sustainability.

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